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ADAPTIVE SELECTION OF AIRCRAFT ENGINE TECHNOLOGIES IN THE PRESENCE OF RISK

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ABSTRACT

The objective of this paper is to describe a method for selecting optimal engine technology solution sets while *simultaneously* accounting for the presence of technology risk. This method uses a genetic algorithm in conjunction with Technology Identification, Evaluation, and Selection methods to find optimal combinations of technologies. The unique feature of this method is that the technology evaluation itself is probabilistic in nature. This allows the performance impact and associated risk of each technology to be quantified in terms of a *distribution* on key engine technology metrics. The resulting method can best be characterized as a concurrent genetic algorithm/Monte Carlo analysis that yields a performance- and risk-optimal technology solution set. This solution set is inherently a *robust* solution because the method will naturally strive to find those technologies representing the best compromise between performance improvement and technology risk. Finally, a practical demonstration of the method and accompanying results is given for a typical commercial aircraft engine technology selection problem.

INTRODUCTION

The identification and selection of key technologies needed for next-generation aircraft engines is one of the most challenging problems faced by engine designers. This is because all parts of an aircraft gas turbine engine are tightly integrated together such that a technology introduced into one part of the system tends to have a ripple effect that impacts many other portions of the system. The results of this rippling effect can be difficult to predict, let alone predict quickly and inexpensively. Yet quick, accurate, and inexpensive evaluations are exactly what the marketplace is demanding in order for manufacturers to remain competitive today.

Moreover, each generation of systems tend to evolve into more complex and intricate designs than the previous generation. As a result, the difficulty in designing and building each successive generation of ever-more capable and sophisticated machines rises exponentially with time. The upshot of this is an increasingly urgent need to find new methods capable of quickly and accurately modeling these complex systems and their associated interactions. This need is categorically prevalent throughout the aerospace industry, but is particularly acute in the aircraft gas turbine industry.

It is axiomatic that the best combination of technology options is inherently a balance of many conflicting objectives and there are typically many more technology options available than resources to develop them. One could therefore characterize engine technology selection as a highly constrained multi-objective combinatorial optimization problem for which traditional gradient-based optimization methods are of little use. However, evolutionary search methods used in conjunction with advanced technology analysis methods are known to be very adept at solving complex engine technology selection problems and have been successfully applied to this end.[1,2]

In their present state, these advanced technology selection methods only address a limited aspect of the technology decision-making process. Specifically, they focus primarily on modeling the "benefit" of the technology impact and have only crude models for the impact of technology risk on the selection of technology concepts. The focus of this research is to integrate a more sophisticated model for technology risk into the existing engine technology selection method. The utility of this method is then demonstrated for a typical commercial engine technology selection problem.

TECHNOLOGY IDENTIFICATION, EVALUATION, AND SELECTION METHOD

The Technology Identification, Evaluation, and Selection (TIES) method is a generic technology evaluation method intended to enable rapid and accurate evaluations of technologies in *any* complex system.[3] The fundamental premise of the TIES approach is the use of technology metrics (the so-called K-factors) as a generic means to quickly and accurately model the impact of a technology at the sub-system level. These sub system impact estimates can then be used as a basis for estimating the system-level impact through the use of a technology impact forecasting (TIF) environment. This TIF is often a metamodel created based on detailed-physics-based models, but can, in theory, be almost any model that links fundamental technology metrics to system level performance figures of merit (FoMs). Construction of a TIF usually involves selecting a set of system performance figures of merit (FoMs) and setting up a detailed analytical model for the baseline system. This model is used in conjunction with response surface methods to create a set of response surface equation metamodels that are a compact representation of a much more complex model. These metamodels are collectively referred to as a TIF environment.

The TIES method has been applied to aircraft gas turbine engine technology selection problems with considerable success. TIES implemented in conjunction with a Genetic Algorithm (GA) optimizer[4] has proven particularly adept at finding the best possible set of technologies to meet any prescribed objective, regardless of system complexity, the number of technology concepts considered, or the number of objectives. This technique is a very valuable tool to assist engine designers in selecting the best possible subset of technologies from a pool of technology options. Moreover, the method is inherently fast and accurate if implemented properly.

MODELING TECHNOLOGY RISK

One of the simplest methods for analyzing technology risk and readiness is NASA's Technology Readiness Level (TRL) scoring system.[5] A TRL is subjective score that rates technologies on a scale of one to nine, with a score of one being highest risk and lowest readiness, while a score of nine is lowest risk and highest readiness. Each score is associated with a specific type of analysis or test activity which is intended to be a reflection of the level of research and development confidence in the technology, as shown in Table 1.

The principal advantages of the TRL scoring system are that it is simple to use, universally recognized/understood in industry, and bases readiness scores on a standardized scale. The principal disadvantages of the TRL scoring system are: 1) inherent subjectivity in the scores; 2) the scores themselves are based primarily on the level of testing accomplished (which does not always accurately indicate the true level of risk); 3) TRL scores do not directly model the true nature of risk (i.e.- uncertainty in ultimate benefit); and 4) TRL scores do not account for the myriad of non-technical factors that contribute to technology risk. Therefore, the TRL scoring system should be regarded as a crude but inexpensive proximal treatment of the general technology risk problem.

TRL scores can be very useful in selecting technologies for complex systems, especially in the early phases of the design process where detailed information is rare and timely decisions are of the essence. One can typically obtain good estimates on TRL scores for a variety of technologies in very short order by polling technology experts on their perceptions of a given technology's readiness. These scores essentially categorize technologies according to the perceived risk posed by each.

Table 1 NASA Technology Readiness Level (TRL) Scores.

TRL	Description
9	Actual System Flight Proven on Operational Flight
8	Actual System Tested and Flight Qualified
7	System Prototype Demonstrated in Flight
6	Model or Prototype Demonstrated in a Relevant Environment
5	Component Validation in a Relevant Environment
4	Component Validation in a Laboratory Environment
3	Analytical and/or Experimental Proof-of-Concept
2	Technology Concept Formulated
1	Basic Principles Observed and Reported
0	No Concept Formualtion - Only basic Ideas

This TRL rating system can be used directly in the GA-TIES analysis method as a crude model for risk by using the TRL (in conjunction with other performance figures of merit) as a component in a composite objective function. The resulting technology solution set is optimal in that the performance benefits are balanced against the TRL score in proportion to user-specified weights applied to the objective function. This approach was implemented and demonstrated in Ref. 1 on a commercial aircraft engine technology selection problem using a GA-TIES method and was shown to be capable of finding solutions that are difficult or impossible to obtain using conventional perturbation-based technology selection methods.

However, the GA-TIES method as demonstrated in Ref. 1 has a critical drawback. The simple model for technology risk based strictly on TRL scores does not capture the fundamental nature of technology risk, which is essentially degradation of expected benefit. In other words, the higher the risk, the more the expected benefit must be discounted. What is required is a *simple*, *compact* model for technology risk that captures the degradation of expected benefit, such as the K-σ risk model described in the following section.

THE K-σ TECHNOLOGY RISK MODEL

The K-σ model was for technology risk was first proposed by Kirby and Mavris and could be characterized as an *indexed benefit degradation model* based on TRL score.[6] In other words, the K-σ model probabilistically degrades expected technology benefit as a function of TRL score. To understand this, consider Fig. 1, which shows the expected benefit in terms of a single technology metric (K-factor) for some arbitrary technology. If this technology were at a TRL of 9, one would expect that its benefit relative to the baseline would be precisely known with very high confidence. In the example of Fig. 1, the technology benefit at a TRL of nine is shown as a 20% improvement over the baseline technology.

If the TRL of the technology in Fig. 1 were less than nine, one would intuitively expect that the point estimate on K-factor benefit would not be as precisely known and might better be described as a probability distribution. For the sake of argument, presume that the upper bound of the K-factor range is given by the baseline case (if it were higher, this would imply a trivial solution - the baseline case would be a better performer than the one with technology). Similarly, presume that the lower limit is given by the actual benefit at a TRL of 9. A probability distribution describing the expected benefit must be bounded by these extremes, and the TRL score of that technology dictates the skewness of the distribution towards one limit or the other. This is shown in Fig. 1 as a series of skewed probability distributions, with the distribution being skewed increasingly towards the left as TRL increases.

The distribution used in the K-σ readiness model is usually a Weibull because it can easily be skewed through use of parameters inherent to the distribution, though other distributions could be used if desired. The general form of the equation describing a Weibull distribution on K-factors as a function of TRL is given by:

$$k_i(\mathrm{x})\Big|_{T_i} = \begin{cases} \left(\dfrac{2}{\alpha}\right)\left(\dfrac{\mathrm{x}-k_i}{\alpha}\right)\exp\left(-\left(\dfrac{\mathrm{x}-k_i}{\alpha}\right)^2\right) & \mathrm{x} \geq k_i \\ 0 & \mathrm{x} \leq k_i \end{cases} \tag{1}$$

where α is a scale parameter:

$$\alpha\Big|_{k_i, T_i, L=k_i, \beta=2} = \left|30\% k_i\right| - (TRL-1)\frac{\left(\left|30\% k_i\right| - \left|5\% k_i\right|\right)}{8}$$

Note that the bounds prescribed in the above equation could be changed if desired and will likely depend on the specifics of the problem being considered. However, the settings given above are generally a good starting point for any given K-factor.

The K-σ model offers a realistic means of simulating the impact of technology risk through probabilistic degradation of benefit. It is very flexible and simple, and though the example given here is applied to a single K-factor, it is easily extended to more complex technology models involving multiple K-factors. Note that the K-σ model is slightly conservative in its allowance for technology benefit, due primarily to the considerable degradation in K-factor benefit in moving from a TRL of 9 to 8. The bounding model assumed in this example can be modified to reach outside the baseline and nominal benefit limits if so desired. This paper will implement this technology readiness model as part of the GA-TIES technology selection method.

K-σ/GA-TIES ANALYSIS METHOD

The K-σ technology risk model can be integrated into the TIES methodology in a fairly straightforward manner. To understand how this can be done, first consider the GA-TIES method as it is used today. Typically, when a TIES study is used to find an optimal technology set, the first step is to decide on a set of technology K-factors that will be used to model the technologies. Next, a pool of promising technology concepts is created and the impact of each technology under consideration is quantified in terms of deltas in these K-factors. This is usually achieved via a delphi-type exercise involving a group of technology experts. The resulting K-factor data is then assembled into a technology impact matrix (TIM). Once this is done, technology incompatibilities and enabling relationships are identified and encoded in the form of a compatibility matrix and an enabling matrix. Finally, each of the technologies is scored on a TRL rating scale.

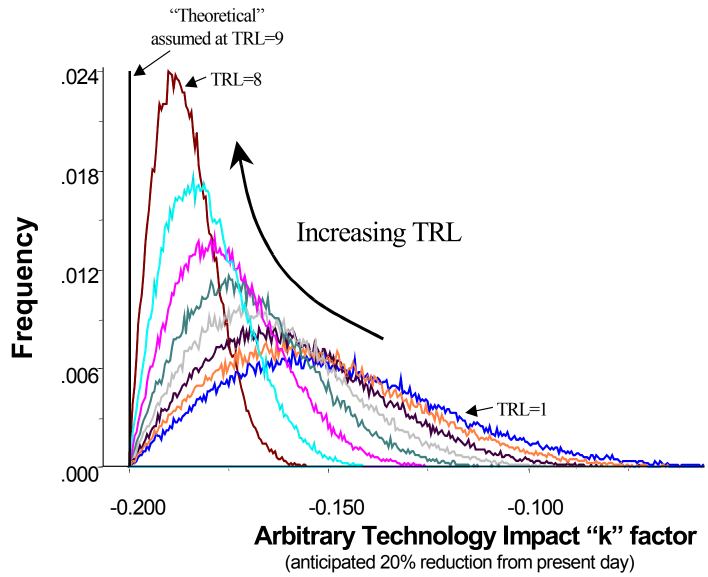

Fig. 1 K-σ Model for Technology Readiness (From Kirby and Mavris, Ref. 6).

At this point, all of the basic characteristics of the technologies have been encoded into a few matrices of numbers that embody the fundamental nature of each technology. These matrices can be quickly and accurately evaluated to calculate benefit of any arbitrary combination of technologies, provided that a technology impact forecasting (TIF) model is available. As mentioned previously, a TIF is essentially nothing more than a set of response surface equations for the system performance FoMs as a function of the K-factors.

The technology representation for any given technology in the candidate pool consists of a vector of point estimates on K-factor deltas as illustrated in Fig. 2. These point estimates can be plugged into the TIF model to yield point estimates on how each technology impacts overall system performance. This information can then be used in conjunction with the TRL scores as components in an objective function for GA optimization. The GA operates on the TIES model by picking various combinations of technologies, analyzing the results, and comparing their fitness using an objective function that is a linear combination of the various FoMs:

$$obj = \alpha\left(\sum_i 10 - TRL_i\right) + \beta(FoM1) + \gamma(FoM2) + \ldots \tag{2}$$

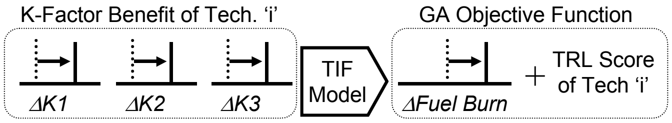

Fig. 2 Typical TIES Representation of Technology in Terms of Point Estimates on K-Factor Deltas.

The K-σ model for technology risk builds on this basic process by using the TRL scores as a basis to introduce a probabilistic degradation of the K-factor vectors associated with each technology. The lower a technology's TRL, the more the K-vector is degraded from the nominal benefit. This concept is illustrated in Fig. 3, which shows the K-vector for a given technology being expressed in terms of distributions on the K-factor deltas. The resulting performance will necessarily be a distribution of values as well. Since the technology readiness is explicitly encoded into the TIES model, it is not necessary to use TRL as a component in the GA objective function. Instead, the objective function can now be a pure linear function of performance FoMs:

$$obj = \beta(FoM1) + \gamma(FoM2) + \delta(FoM3) + \ldots \qquad (3)$$

The primary difference in the two formulations as far as the genetic algorithm is concerned is that in the former scheme, the objective function was purely deterministic – the TIES model always returns the same value for technology benefit for a given the set of technology inputs. The K-σ model will *never* return the same value for technology benefit twice, even if identical technology inputs are evaluated repeatedly. This is because the distributions on K-factors effectively introduce an element of random noise into the objective function evaluation.

The advantage of a GA-enabled technology selection is that it works on *populations* of designs that are evolved over many generations. Thus, the presence of noise in the objective function evaluation does not impede the GA's march toward a global optimum. Even though no single comparison between two technology sets will yield precisely the same result, the GA will still find the set of technologies that optimizes the objective function *in the mean*. Moreover, this final solution will naturally tend towards the most *robust* solution, which is the solution that exhibits the best compromise between minimum design variation and maximum performance benefit.

APPLICATION TO A TYPICAL COMMERCIAL ENGINE TECHNOLOGY SELECTION PROBLEM

Perhaps the most expedient means of illustrating this model and its advantages is to demonstrate it on a typical technology selection problem of current interest. The objective of this section is to do precisely that. It should be noted that this problem is quite representative of those encountered in industrial practice, and is in fact based on a larger study conducted by the authors for GE Aircraft Engines.

Problem Description

The technology study considered is based on that described in Ref. 1 and consists of a set of 40 technology

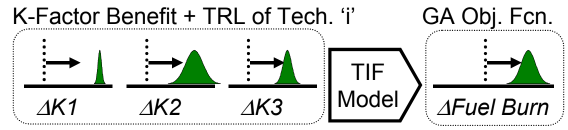

Fig. 3 Calculation of Technology Benefit Using the K-σ Technology Readiness Model.

concepts. This includes 10 high pressure compressor technologies, 4 combustor technologies, 9 high pressure turbine technologies, 7 frame/sump/bearing technologies, and 10 low pressure spool technologies. These technologies were selected and evaluated in conjunction with experts from GE Aircraft Engines. The technology metrics used to evaluate technology impact consist of 11 factors, listed in Ref. 1, and were assembled into a 11X40 TIM such that each row contained all information necessary to evaluate a single technology in the TIF model.

The baseline engine is a current state-of-the-art high bypass commercial turbofan engine and the baseline aircraft is a notional twin engine long range wide-body commercial transport. The primary performance figure of merit of interest for this problem is change in 6,000 nmi mission fuel consumption relative to the baseline (no technologies) configuration. In addition, each technology was rated using TRL scores for technology risk and a "relative shop cost score". The former was described previously, while the latter is an ordinal ranking on manufacturing cost of each technology relative to the current technology baseline. For example, a score of "0" would indicate a technology of comparable manufacturing cost to current methods, a "+1" would indicate slightly higher cost, "+2" is much more costly, etc. The analysis model and setup is described in detail in Ref. 1.

Results

The 40-technology problem described previously was evaluated for several scenarios such that the differences in results could be compared to deduce the impact of implementing the K-σ technology risk model. Specifically, three scenarios are evaluated: a reference case in which the technology selection was based purely on 6K fuel burn and relative shop cost only (meaning TRL is not used in the objective function); a simple TRL treatment wherein TRL is used as one of the components in the GA objective function; and a final case wherein the K-σ model is used.

One might intuitively expect that the "no-risk model" reference case will tend to be the solution incorporating the most technologies. This is because the objective function only forces the GA to balance the undiscounted technology benefit against relative shop cost. In the other extreme, if TRL is included in the objective function with a weight equal to both shop cost and 6K fuel burn, one would expect that any technology with a low TRL score would be eliminated quite readily unless it showed exceptional potential for improving either shop cost or performance.

The analysis results for these two cases indicate that this is precisely the case. The results for the no-TRL case are shown

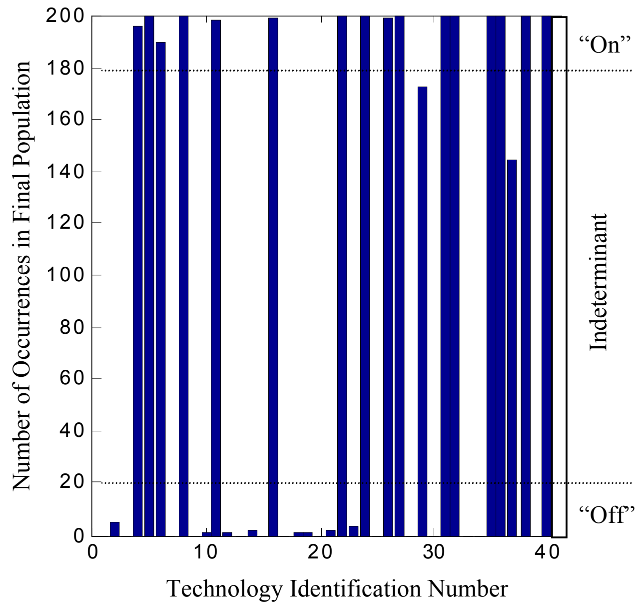

Fig. 4 Converged Technology Solution Set for Shop Cost+Fuel Burn Objective Function.

in Fig. 4 and typical convergence histories for fuel burn and shop cost as a function of number of generations is shown in Fig. 5 and Fig. 6, respectively. Fig. 4 is a bar chart showing which technologies were selected by the GA. The abscissa of this chart is a technology label, numbered from 1 to 40. The ordinate of the chart shows the number of occurrences each technology was present in the final (converged) population. In this case, the population size was set at 200, so a technology having a score of 200 in Fig. 4 indicates that that technology was uniformly present in the converged population. Similarly, a score of zero indicates that the technology was extinct from the final population, implying that it was not desirable for improving the objective function.

Since the genetic algorithm injects mutations into the population with a relatively high probability (20% in this case), there is some degree of random noise in the final solution. Consequently, a technology that is present in 90% or more of the final population (i.e. a score of greater than 180) is taken to be part of the optimal technology solution set whereas any technology not present more than 10% of the time is taken to be excluded from the optimal set. Scores of between 10% and 90% are indeterminate. Thus, Fig. 4 indicates that technologies 4, 5, 6, 8, 11, 16, 22, 24, 26, 27, 31, 32, 35, 36, 38, and 40 are part of the optimal technology solution set if relative shop cost and fuel burn are the only considerations in the objective function. Technologies 29 and 37 are indeterminate.

The convergence histories given in Fig. 5 and Fig. 6 give some insight as to how the GA arrived at this solution. These figures show a precipitous drop in both objective functions during the first 50 generations, indicating that the GA is finding technology combinations that benefit both objectives. After generation 50, the solution is largely converged, as evidenced by the relatively narrow average dispersion between the minimum, maximum, and average objective in the population. One can see that in the last 150 generations the average shop cost decreases slightly at the expense of a slight increase in fuel consumption, indicating that the GA is finding it desirable to trade some performance in the interest of reduced cost.

The solution for the shop cost/fuel burn/TRL case is shown in Fig. 7. In this case, TRL is given an objective weighting equal to fuel burn and shop cost (i.e. 1/3 weight on each). The change in the optimal technology solution set is precipitous, as evidenced in Fig. 7. In this case, only technologies 22, 26, 27, and 38 are selected, with all others being rejected. The convergence history for this case is similar to that shown in Fig. 5 & Fig. 6 and is not shown in the interest of brevity.

The results for the GA solution incorporating the K-σ model are shown in Fig. 8. As one might expect, the results are somewhat intermediate relative to the previous scenarios. In this case, technologies 4, 5, 16, 22, 24, 26, 27, 31, 32, 35, 38,

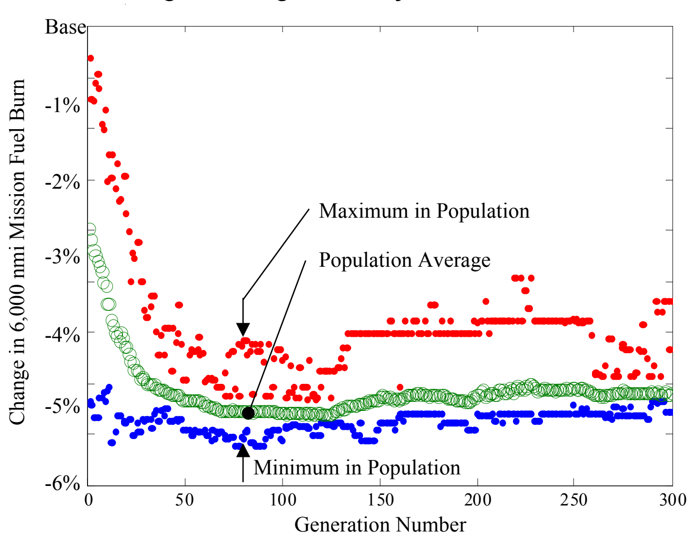

Fig. 5 6,000 nmi Mission Fuel Burn Convergence History for 50% Shop Cost + 50% Fuel Burn Objective Weights.

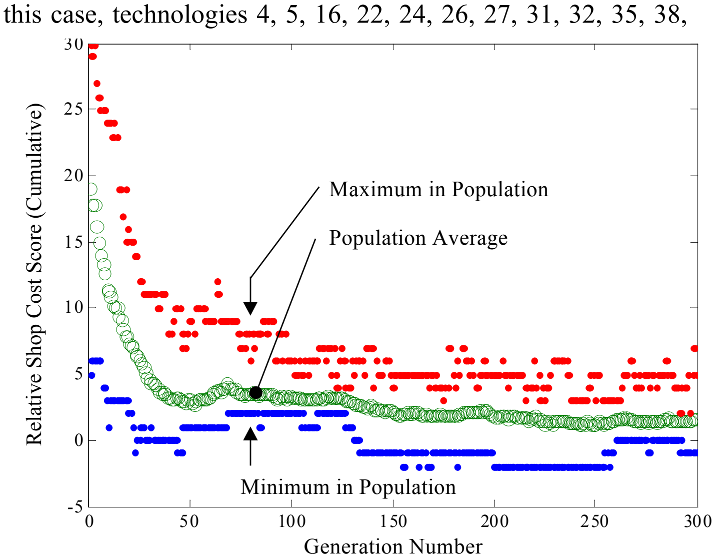

Fig. 6 Relative Shop Cost Convergence History for 50% Shop Cost + 50% Fuel Burn Objective Weights.

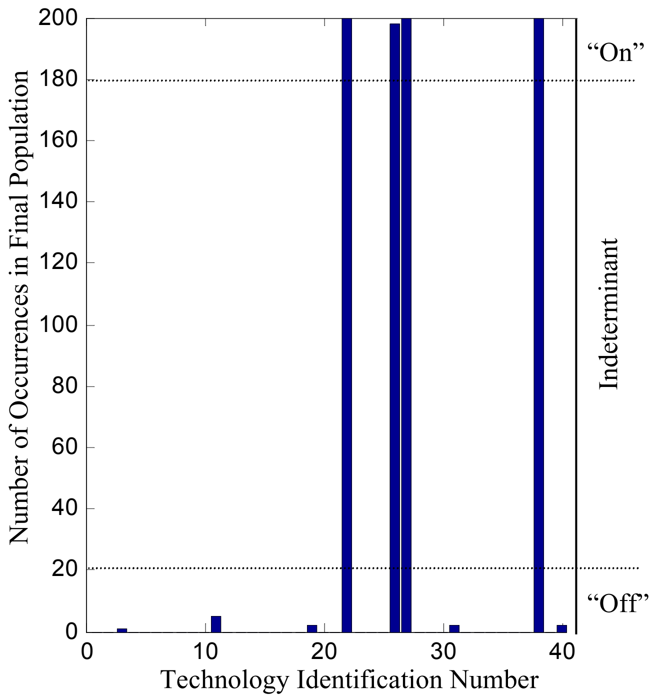

Fig. 7 Converged Technology Solution Set for 33%Shop Cost + 33%Fuel Burn + 33%TRL Objective Weights.

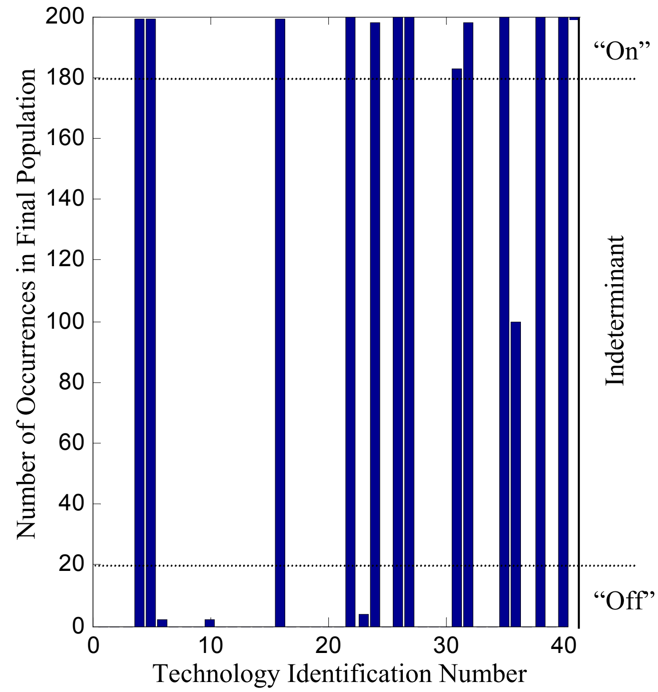

Fig. 8 Converged Technology Solution Set for Shop Cost+Fuel Burn Objective Function with K-σ Risk Model.

and 40 are optimal relative to the objective function, which includes only fuel burn and relative shop cost. The impact of the K-σ model in practice is to degrade the fuel burn benefit obtained from the technologies, so it is perhaps no surprise that the results obtained with this model are intermediate.

The end result of this analysis is a technology set that can serve as a starting point to begin more detailed technology trade studies. In this regard, the method described herein could be thought of as a screening tool for technologies not unlike the perturbation-based technology analysis methods used today. However, the methods described herein also account for risk as well as the various compatibility and enabling relationships amongst technologies, whereas classical methods do not. For small studies involving only a handful of technology options, it is possible to devise "one-on" and "one-off" perturbation studies that account for these relationships. However, as the number of technologies under consideration increases, the classical methods become increasingly limited in the scope and accuracy of their results. The present method has no such limitation.

CONCLUSIONS

- The solution obtained using the K-σ model for technology risk is truly the robust solution: the optimal compromise between technology uncertainty and performance benefit.
- The K-σ model provides a good compromise between expediency (available with the TRL approach) and accuracy (enabled through mapping of distributions to TRLs).
- K-σ model as implemented herein should provide a slightly conservative estimate of which technologies benefit a given objective function. This is useful in determining which subsets of technologies are most promising to be carried forth into detailed product development.
- The applicability of the GA-Monte Carlo method is broader than technology risk. The technique can be used to find a robust solution to *any* engine design problem.
- Provides a first step towards the development of even more sophisticated and capable analysis methods that would have provisions for other factors that must be considered in technology selection, particularly technology impact on *budget, schedule,* and *manpower/resources available*.

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